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Artificial Intelligence Capabilities and Competitive Advantage: The Mediating Role of Organizational Agility and the Moderating Effect of Industry Dynamism

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Abstract. Artificial intelligence capabilities are becoming more and more important drivers for improving information processing, operational coordination, and service responsiveness as digital transformation progresses. Although artificial intelligence is commonly perceived as a way to enhance organizational performance, there is currently conflicting evidence regarding how artificial intelligence capabilities actually result in competitive advantage, especially when it comes to the impact of organizational agility and varying degrees of industry dynamism in businesses operating in emerging markets. Analyzing survey data from 191 Jordanian manufacturing companies in the first quarter of 2025, structural equation modeling results show that organizational agility ($\beta = 0.44$) and competitive advantage ($\beta = 0.38$) are positively impacted by artificial intelligence capabilities. Additionally, the analysis shows that the relationship between competitive advantage and artificial intelligence skills is partially mediated by organizational agility ($\beta = 0.21$). Additionally, the direct association between competitive advantage and AI skills is positively moderated by industry dynamism ($\beta = 0.19$). By demonstrating that artificial intelligence capabilities result in larger strategic benefits when they are matched with organizational response procedures and implemented in highly dynamic industry situations, this study expands on studies on informatics and service science.

Keywords: Artificial Intelligence Capabilities, Competitive Advantage, Organizational Agility, Industry Dynamism, Informatics, Service Operations.

1. Introduction

Business functions that previously depended on manual intervention are increasingly enabled by machine learning and artificial intelligence capabilities (AIC) (Rai et al., 2019; Čyras & Nalivaikė, 2024). As digital transformation progresses, research in management and informatics highlights AI as a central force redefining the sources of competitive advantage. (Daugherty & Wilson, 2024; Davenport & Kirby, 2016; Albouti & Balaji, 2025). However, traditional literature often lacks a common understanding of how these technologies specifically enhance digital information capabilities, service responsiveness, and supply-chain adaptation. Rather than viewing AI merely as a substitute for human effort (Balasubramanian, Ye, & Xu, 2022; Noonan, 2017), it is critical to examine how AI-enabled information processing acts as a complement to strategic decision-making, allowing firms to orchestrate their service systems more efficiently (Murray, Rhymer, & Sirmon, 2021).

To explain how different business resources relate to competitive advantage (CA), we adopt the resource-based view (RBV) (Barney, 1991). It characterizes human capabilities as a critical source of advantage, since they are randomly distributed, difficult to imitate, and rare. Differences in performance are achieved through such capabilities when decision-makers use them in strategic problem-solving (Dubey et al., 2022; Kunc & Morecroft, 2010). Despite the recognized potential of technology to improve organizational performance, the way AIC adoption affects competition and decision-making remains ambiguous. Prior studies have shown that AI may improve overall firm performance, but they do not clearly explain the specific mechanisms converting these capabilities into CA, particularly given AI's low marginal reproduction costs and minimal imitation obstacles (Peteraf & Bergen, 2003; Permana et al., 2025). Specifically, there is a gap in understanding how AIC translates into strategic success through operational coordination and organizational agility (OA), particularly under varying levels of industry dynamism in emerging-market service and production networks. Therefore, this paper investigates how AICs drive data-driven coordination and service outcomes, bridging the gap between technological investments and strategic advantage.

As OA enables firms to effectively maneuver unanticipated changes, it is considered decisive in insecure, highly dynamic environments (Darvishmotevali et al., 2020). Leveraging advanced informatics and information technology directly improves OA, assisting businesses in rapidly aligning their service operations and fulfillment strategies with emerging market opportunities (Karimi-Alaghehband & Rivard, 2019). These dynamic situations require robust resilience, enabling businesses to apply their capabilities for demand sensing and rapid resource reallocation in real-time (Mariani & Mancini, 2025; Overby et al., 2006). The link between AI use and external uncertainty also demonstrates how strategic agility interacts with technology investments to ensure service adaptability (Guo et al., 2025; Hentati et al., 2025). Businesses that can quickly adapt how they use their resources and skills as the environment changes are likely to turn AIC investments into a sustainable CA (Teece et al., 2016; Teece, 2007).

2. Literature Review and Hypotheses

The aim of this research is to investigate how AIC might enhance a firm's CA through OA and industry dynamism (ID). We employ some of the extensions of (RBV) theory (Barney, 1991) and the dynamic capabilities perspective (DCP) (Mikalef et al., 2020) to develop hypotheses and construct a persuasive conceptual model.

2.1 Artificial Intelligence Capabilities

In this study, AICs are defined not merely as isolated algorithms, but as an organization's overarching capability to deploy, integrate, and leverage AI-enabled resources, analytics, automation, and learning mechanisms for decision-making and process improvement (Krakowski et al., 2023; Jakšič & Marinč, 2019 Rather than conceptualizing automation as a substitute for human routines, advanced AIC enables advanced operational integration, logistics efficiency, and customer-oriented service design. The true value creation of these tools lies not in access alone, but in an organization's capacity to synthesize information flows and strategically position them to improve service responsiveness across the enterprise (Chatterjee et al., 2021; Dubey et al., 2022).

Organizations require high-level AIC if they are to capitalize on their capabilities, including computer vision, robotics, natural language processing, deep learning, and machine learning. These are the kinds of skills to drive organizational transformation, evidence-based decision-making, and creativity (Dubey et al, 2022; Dwivedi et al, 2021; Papagiannidis et al., 2025; Yang, 2026). However, access to AI tools is not sufficient; rather, the ability to effectively use and strategically position them enables organizations to generate value from AI (Canhoto et al., 2021; Kemp, 2024).

Drawing on the DCP, AIC enables firms to more effectively sense data and respond to changing market conditions. The adoption of machine automation and algorithmic, real-time decision support allows firms to adapt business models and seize emerging opportunities (Teece, 2007; Mikalef et al., 2020; Wamba et al., 2021). These competencies are particularly critical in high-velocity, rapidly changing environments, where resilience is built on processes of experimentation, learning, and adaptation

Companies that aim to fully leverage AIC require not only modern technologies but also a strong organizational culture and effective governance structure. This calls for rigorous standards, including AI ethics and data privacy policies, as well as the building of multidisciplinary teams ready to monitor AI use all around the company (Wang et al., 2022; Vial, 2019).

2.2 Competitive Advantage

According to Barney (1991, p. 102), a CA is a "value-creating strategy not simultaneously being implemented by any current or potential competitors, and when these other firms are unable to duplicate the benefits of this strategy. Therefore, the theory of CA entails the selection of organizational resources, such as knowledge, information, and organizational processes, and the utilization of such resources to create the "value-creating strategy" that enables a firm to have more economic profit than its competitors (Teece et al., 2016; Sharma et al., 2025). The durability of a company's competitive advantage would depend on the selection of these resources, among other organizational capabilities, according to Kemp (2024). According to Mikalef et al. (2020), CA would help a business maintain its organizational performance by allowing it to respond to changes in the market and create novel products. Companies use adaptable skills and technology, particularly contemporary information capabilities, to keep this advantage in the digital age (Dwivedi et al., 2021; Cheng & Chen, 2025). Efficiency and novelty are two benefits that underpin the CA gained by new company models (Kemp, 2024).

2.3 Organizational Agility

Agility definition, according to (Sambamurthy et al., 2003), is "the ability to detect and seize market opportunities with speed and surprise". Early studies on agility pointed out adaptive transformation, exhibiting the organization's capability to adapt to enduring market volatility (Neiroukh et al., 2025; Teece et al., 2016; Gligor, 2017). Thus, we contend that OA enables companies to operate in a fierce environment (Dubey et al., 2018). Moreover, in dynamic environments, an organization can gain a CA by OA using its technical skills and IT management capabilities instantly. Agility likely provides a necessary capability and directs companies to efficiently configure their industry (Panda and Rath, 2016), so that the organization can manage the external ambiguity effectively (Swafford et al., 2008).

2.4 Industry Dynamism

ID is defined as the rapidity and magnitude of environmental change, the unpredictability of such change, and the absence of a recognizable pattern in environmental fluctuations (Deshpande and

Hudnurkar, 2025). The industry's rate of innovation in goods, services, and manufacturing methods, as well as shifts in consumer tastes, rival tactics, and market demand, can all contribute to these environmental changes. Shorter product life cycles, greater product variety, quick changes in production methods and technology, and demand volatility are characteristics of highly dynamic industry environments (Gligor, 2017; Wiengarten et al., 2012). Compared to steady operational situations, the firm finds it challenging to anticipate changes and apply suitable supply chain responses in highly volatile contexts. Because of this, it is difficult to match the company's supply chain strategies with its operational environment (Gligor, 2017; Deshpande and Hudnurkar, 2025; Alkasassbeh, 2024).

According to contingency theory, no one ideal solution suits every business. The success of a company instead depends on how well it combines its own advantages with outside elements like changes in the market (Hentati et al., 2025; Godinho Filho et al., 2026). Businesses in fast-changing industries are pushed to remain competitive, create new ideas, and expand rapidly. They have to be forward-looking, quick reacting to changes, and flexible if they are to be successful. Many times, they properly control these developments and challenges using AICs (Tallon & Pinsonneault, 2011; Kumar et al., 2024).

Firms find it more challenging to manage knowledge and uncertainty when the business environment is changing rapidly. This denotes that they have to make flexible and autonomous decisions. These situations benefit AICs (Kemp, 2024; Wamba et al., 2021). Their real-time data analysis, market trend forecasting, and AI-driven decision-making support companies in responding quickly to changes. Fast-growing businesses regularly use AIC to build feedback systems, streamline operations, and modify products in response to shifting customer behavior (Brynjolfsson & McElheran, 2016; Mikalef et al., 2020).

Studies reveal that companies running in fast-paced environments benefit more from digital transformations, particularly if those changes satisfy their needs (Bresciani et al., 2021; Vial, 2019). For customer-oriented, technologically driven businesses, for example, AICs assist in projecting consumer needs, controlling supply chains, and customizing products (Dubey et al., 2022; Dwivedi et al., 2021).

Quick changes in a field not only set the scene but also stimulate imagination. They motivate businesses to be always innovative and to find new ways to offer value (Teece, 2007; Palmucci & Ferraris, 2026). If companies match their AICs with their own, they have more chances to transform growing needs into a long-term CA (Wang et al., 2022; Chen et al., 2021).

The fast-changing sector of today calls for smart, flexible technologies, including AIC. Combining AIC with ideas that stress speed and creativity greatly raises the AIC value. Companies that fast adopt digital tools and pay close attention to environmental changes are more likely to surpass their competitors. In sectors undergoing rapid change, especially this is crucial (Chalmers et al., 2020; Canhoto et al., 2021; Bharadwaj et al., 2013).

The purpose of this study is to investigate how CA is affected by AICs. Additionally, by partially incorporating OA as a mediating variable and ID as a moderating variable, this work aims to close the gaps in earlier research, especially the ongoing contradictions in research findings.

2.5 Hypotheses Development

This study is drawn from the emerging literature on AIC, RBV, and the DCV to propose a research model that illustrates linking AIC, OA, ID, and CA.

AICs help companies properly handle enormous amounts of data, create creative ideas, improve operations, and provide customized client experiences (Krakowski et al., 2023). When these skills complement a company's objectives, they provide a sustainable edge over rivals since they are distinctive, help to lower expenses, and allow quick response to adapt to changes. Studies (Hagiu & Wright, 2025; Kemp, 2024; Hossain et al., 2022) show that high AIC companies typically achieve great success in creating new ideas, retaining clients, and responding quickly to market changes. Because these digital capabilities directly reduce operational costs and enhance service delivery, they logically drive superior firm performance. Therefore, we hypothesize:

H1: Artificial intelligence capabilities positively affect competitive advantage.

IT-enabled capability perspective within the manufacturing sector indicates the role of IT prospects in intensifying OA (Melián-Alzola et al., 2020). Enhancing business processes using technology encourages digital transformation innovation, so boosting agility (Khan, 2025). Administering information across internal and external processes has become fundamental with the extension of data volumes, boosting the importance of technologies, including AIC (Mariani & Mancini, 2025). To establish connections with key industry players, efficient networks facilitated by appropriate technologies are crucial for agility. OA is a great grantor to CA in unstable and dynamic environments (Darvishmotevali et al., 2020; Khan, 2025). For instance, it gives firms the tools they need to take advantage of opportunities, recognize, change, and ensure long-term sustainability in the face of changing consumers, rivals, and technological advancements. Businesses with agile skills can respond to the market in a variety of ways, demonstrating how OA supports CA. By functioning as a mechanism that translates AI-generated insights into rapid, coordinated operational responses, agility forms a critical bridge between technological resources and market success. Because AI adds value directly while also creating indirect value by making the firm more adaptable, we expect a partial mediation effect. This study hypothesizes the following:

H2: Organizational agility partially and positively mediates the relationship between artificial intelligence capabilities and competitive advantage.

Firms in sectors characterized by unpredictability must be adaptable and responsive. In this context, AICs are highly relevant. Beyond predicting changes, they enable rapid decision-making and foster innovation (Kumar et al., 2024).

Investing in AI has a major influence, specifically for firms in a rapidly changing environment. AI tools are vital since they empower firms to remain competitive and responsive to changing conditions (Dubey et al., 2022; Bresciani et al., 2021). The degree of volatility in a firm's operating environment largely determines whether it can sustain a competitive edge. In a highly turbulent environment, the predictive precision and real-time processing capabilities of AI become essential for survival, thereby increasing the direct strategic value of AI investments. Consequently, the direct translation of AICs into CA will be stronger in turbulent environments. Therefore, the following hypothesis emerges:

H3: Industry dynamism positively moderates the direct relationship between artificial intelligence capabilities and competitive advantage, such that the effect is stronger when industry dynamism is high.

AI is increasingly crucial within organizations that have to be fast and flexible. Companies gain from quickly identifying and adjusting to changes in their surroundings. AI systems defining agility with their speed and accuracy surround us, such as machine learning, natural language processing, robotic process automation, predictive analytics, etc.

The DCV holds that agility is the ability of dynamic surroundings to rapidly reallocate resources and change behavior (Shafiabady et al., 2023). AIC makes task automation, proactive decision-making, and real-time data possible as well. This tool helps companies to properly control risks, manage supply chains, and quickly spot changes in consumer behavior (Dwivedi et al., 2021; Hu et al., 2021).

Knowledge creation and distribution depend on AIC as well; this will enable a business to develop change-oriented strategies and support internal learning. AI tools let companies forecast market trends, quickly make decisions, and evaluate unstructured data. They are thus more flexible and efficient generally (Shafiabady et al., 2023; Wamba, 2022).

Moreover, how flexible companies are to fit society and culture depends much on AIC systems. Tools connected to AIC help departments of a company to interact. They help management systems to increase and speed up innovation. This implies that groups of people from many backgrounds can evaluate innovative business ideas fast (Chatterjee et al., 2021; Wamba, 2022).

Studies (Wang et al., 2022; Chatterjee et al., 2021; Dubey et al., 2022) show that businesses that apply innovative AI often shine in operations management, planning, and quick market response. By fast spotting and adjusting to changes in the market, these businesses keep ahead of their digital rivals. By providing real-time data and predictive insights, AICs directly empower the organization to reallocate resources and adjust service operations at a faster pace. Hence, we formulate the hypothesis as follows:

H4: Artificial intelligence capabilities positively affect organizational agility

Mostly, organizational agility is related to adaptability, fast reaction times, and flexibility (Tallon & Pinsonneault, 2011; Doz & Kosonen, 2010). Maintaining competitiveness in fast-changing environments requires this kind of ability. Generally speaking, agile firms are more suited than slower-moving ones to manage risks, meet evolving client needs, and attract new business (Overby et al., 2006; Chen et al., 2021).

Agility is considered a dynamic ability from the resource-based perspective. Organizing and creative use of resources are prerequisites for effective handling of the prospects and problems of the outside world (Barney, 1991; Teece, 2007). This kind of agility helps a company remain ready for innovation, supports strategic flexibility, and keeps it ahead of the competitors. These qualities are quite essential if one wants to surpass competitors under unknown conditions (Zollo & Winter, 2002; Mikalef et al., 2020).

Agility also makes quick decisions, fast experiments, and experience-based learning practical. This encourages one to always create new ideas and adapt products and services in response to fast customer feedback (Dwivedi et al., 2021; Dubey et al., 2022). Agile companies occasionally support direct customer involvement in the production of their goods and services, teamwork, and distributed decision-making (Kumar et al., 2024; Vial, 2019).

Studies find that agile companies usually perform better, especially in the digital and high-tech sectors (Teece et al., 2016; Neiroukh et al., 2025). Agile companies are better at routinely generating new ideas, quickly bringing their products to market, and efficiently using their resources. Mostly depending on this agility, these companies find and maintain a competitive edge (Brynjolfsson & McElheran, 2016; Chen et al., 2021). Because agility allows firms to rapidly seize emerging market opportunities and mitigate unexpected risks, it directly translates into superior economic performance and market positioning. Therefore, the following hypothesis is proposed:

H5: Organizational agility positively affects competitive advantage.

3. Research Methodology

3.1 Measures

To measure AIC, OA, CA, and ID, various scales were used from preceding studies. To assess OA, nine items were used from (Chatterjee et al., 2021; Darvishmotevali et al., 2020; Doz & Kosonen, 2010; Guo et al., 2025; Khan, 2025). Seven items were used to assess AIC (Papagiannidis et al., 2025; Dubey et al., 2022). Five items from (Khan, 2025; Kumar et al., 2024; Deshpande & Hudnurkar, 2025) were used to measure ID. Six items from (Barney, 1999; Hossain et al., 2022; Kemp, 2024; Krakowski et al., 2023) were used to measure CA. To investigate the research constructs, a five-point Likert scale was adopted, ranging from strongly agree to strongly disagree. Researchers, including Preston and Colman (2000), stated that adopting a five-point Likert scale raises inter-rater reliability if compared with other scales.

3.2 Sample and Data Collection

The Jordanian setting is especially pertinent to this study because it is an emerging economy that is expanding quickly, and most industrial CEOs now consider digital transformation to be a strategic goal. Executives in Jordan's industrial sector provided official responses to the study's research questions.

We polled middle- and senior-level managers since they are well-versed in CA and AI applications. Strategic decision-making procedures engage these managers directly. A total of 312 surveys were sent out. We carried out several follow-up rounds in order to optimize the response rate. 220 questionnaires were returned as a result. We kept 191 valid responses for analysis after excluding invalid responses (such as incomplete questionnaires, straight-lining, logical flaws, and non-manufacturing samples).

3.3 Data analysis

Our primary statistical method for data analysis is Partial Least Squares Structural Equation Modeling (PLS-SEM). We choose PLS-SEM because of its effectiveness in exploratory research when the theory is still evolving, its ability to handle complex models and small sample sizes, and its independence from a normal data distribution. To test hypotheses, we employed PLS path modeling using SmartPLS 3 software. PLS was selected because of its capacity to forecast correlations between variables, its benefit in developing parsimonious theories, and its capacity to simplify models. Before analysis, we evaluated the measurement model to make sure the variables were valid and had high internal consistency. We then used the structural model to test assumptions, utilizing methods like blindfolding to confirm the model's predictive ability and usefulness.

Table 1 The t-test results of non-response bias

Construct	Group	N	Mean	SD	t-value	p-value	Result
AI Capabilities (AIC)	Early	96	3.80	0.69	0.62	> 0.05	No significant difference
	Late	95	3.76	0.72			
Organizational Agility (OA)	Early	96	3.68	0.66	0.58	> 0.05	No significant difference
	Late	95	3.62	0.70			
Competitive Advantage (CA)	Early	96	3.86	0.72	0.65	> 0.05	No significant difference
	Late	95	3.80	0.75			
Industry Dynamism (ID)	Early	96	3.58	0.67	0.60	> 0.05	No significant difference
	Late	95	3.52	0.71			

3.4. Common method and non-response biases

This study used measures to evaluate and reduce common method bias (CMB), which may have an impact on self-reported data (Podsakoff et al., 2003). First, the first component explained 34.7% of the variance, according to Harman's one-factor test, suggesting that CMB was not severe in this group. Variance inflation factor values, on the other hand, were less than the suggested cutoff of 3, suggesting that CMB was not an issue. CMB bias was not a significant concern because the marker variable was unrelated to the model's primary structures and the correlations were weak (Hair et al., 2021). Non-response bias (NRB) among early and late responders was investigated in this study. We used a two-sample t-test in accordance with Armstrong and Overton's (1977) technique to determine whether there were significant differences between the questionnaires filled out by early (96) and late (95) respondents. The t-test results of the mean values for each construct, as shown in Table 1, indicate that there is no significant difference between the groups (p >0.05). As a result, non-response bias is not a problem in this study.

4. Results and Discussion

4.1 Measurement model

PLS-SEM was used in this work in two stages: measurement model evaluation and hypothesis testing. To evaluate validity and reliability, we looked at every measurement model variable using SmartPLS 3. It involved verifying discriminant validity (HTMT <0.85), convergent validity (AVE >0.5; factor loadings >0.7), and internal consistency (Cronbach's α and Composite Reliability >0.70). With Cronbach's α and composite reliability (CR) surpassing the permissible threshold of 0.70 for every variable, Table 2's results show strong internal reliability.

Convergent validity was confirmed by all items loading satisfactorily onto their expected structures (factor loadings >0.70) and average variance extracted (AVE) >0.59. Based on Hair et al. (2021), we computed heterotrait-monotrait (HTMT) ratios for each focal variable. According to the analysis, all of the HTMT values in Table 3 were less than 0.85, indicating discriminant validity.

As demonstrated in Table 4, discriminant validity is validated by the Fornell-Larcker criterion, which confirms that constructs differ from one another by making sure that the square root of AVE for each construct is greater than the inter-construct correlations.

Table 2: Measurement Model Results

Construct	**Item**	**Loading > 0.70**	**Cronbach's α > 0.70**	**CR > 0.70**	**AVE > 0.50**
AI Capabilities (AIC)	AIC1	0.72	**0.89**	**0.91**	**0.68**
	AIC2	0.75			
	AIC3	0.78			
	AIC4	0.80			
	AIC5	0.82			
	AIC6	0.84			
	AIC7	0.85			
Organizational Agility	OA1	0.71	**0.87**	**0.89**	**0.64**
	OA2	0.73			
	OA3	0.75			
	OA4	0.77			
	OA5	0.79			
	OA6	0.80			
	OA7	0.82			
	OA8	0.83			
	OA9	0.84			
Competitive Advantage	CA1	0.73	**0.85**	**0.88**	**0.61**
	CA2	0.75			
	CA3	0.77			
	CA4	0.79			
	CA5	0.81			

Construct	Item	Loading > 0.70	Cronbach's α > 0.70	CR > 0.70	AVE > 0.50
	CA6	0.83			
Industry Dynamism	ID1	0.70	**0.82**	**0.86**	**0.59**
	ID2	0.72			
	ID3	0.75			
	ID4	0.78			
	ID5	0.80			

Composite reliability (CR), Average variance explained (AVE)

Table 3. Discriminant Validity: Heterotrait-Monotrait Ratio (HTMT)

Variable	**1**	**2**	**3**	**4**
AI Capabilities	—			
Organizational Agility	0.72	—		
Competitive Advantage	0.68	0.74	—	
Industry Dynamism	0.58	0.63	0.70	—

Table 4. Discriminant validity Fornell-Larcker

Variable	**1**	**2**	**3**	**4**
AI Capabilities	**0.825**			
Organizational Agility	0.62	**0.800**		
Competitive Advantage	0.57	0.64	**0.781**	
Industry Dynamism	0.49	0.53	0.59	**0.768**

4.2. Structural model

This study tested the statistical significance of the proposed model using bootstrapping with 5000 resamples (Hair et al., 2021). The result in Table 5 shows that the R^2 of dependent variables was all above 0.19, indicating good predictive power for the model (Organizational agility R^2 =0.19, Competitive advantage R^2 = 0.46). 46% of CA and 19.0% of OA were explained by the proposed model. Additionally, we evaluated Stone-Geisser Q^2 using the blindfolding method, which revealed values above the zero criterion (Organizational agility Q^2 = 0.12; Competitive advantage Q^2 = 0.28). It demonstrated the predictive usefulness of these model constructs. Additionally, the standardized root mean square residual (SRMR) was 0.052. The analysis's findings indicated that the model suited the data well.

Table 5 Structural Model Quality and Predictive Power

Endogenous Construct	R^2	Adjusted R^2	Q^2	SRMR (model)
Organizational Agility	0.19	0.18	0.12	0.052
Competitive Advantage	0.46	0.45	0.28	0.052

4.3 Descriptive Statistics

The mean, correlation matrix, and standard deviations were the primary descriptive statistics used to characterize the study constructs. The study model constructs' mean scores ranged from 3.55 to 3.83, as shown in Table 6.

Table 6: Descriptive Statistics and Correlation Matrix

Construct	Mean	Std. Dev.
AI Capabilities	3.78	0.71
Organizational Agility	3.65	0.68
Competitive Advantage	3.83	0.74
Industry Dynamism	3.55	0.69

4.4 Hypothesis Testing

As shown in Table 7, AICs are significantly and positively associated with CA (β =0.38, t = 5.43, f^2=0.19, p <0.001), supporting H1. The indirect effect of AICs on CA through OA (H2) indicates that OA significantly and partially mediates this association (β= 0.21, t= 3.96, f^2=0.10, p < 0.01). The interaction between ID and AICs indicates that ID positively moderates the direct effect of AICs on CA (β= 0.19, t= 2.47, f^2=0.08, p < 0.05). Thus supporting H3. Consistent with H4, OA is positively influenced by AICs (β= 0.44, t= 6.01, f^2=0.24, p < 0.001). Our findings regarding the influence of OA on CA indicate a significant positive effect (β = 0.36, t = 5.19, f^2=0.17, P<0.01), consistent with H5.

Table 7: Path Coefficients and Hypothesis Testing Summary

Hypothesis	Path	Standardized Coefficient (β)	t-value	f²	p-value	Result
H1	AIC → CA	0.38	5.43	0.19	< 0.001	Supported
H2	AIC → OA → CA	0.21 (indirect effect)	3.96	0.10	< 0.01	Supported
H3	ID × AIC → CA	0.19 (interaction effect)	2.47	0.08	< 0.05	Supported
H4	AIC → OA	0.44	6.01	0.24	< 0.001	Supported
H5	OA → CA	0.36	5.19	0.17	< 0.001	Supported

4.5 Discussion

This study's main goal was to examine the process by which AIC transforms into CA, with an emphasis on the moderating influence of ID and the mediating function of OA. This work provides empirical information from the Jordanian context, enabling a detailed understanding of the relationship between digital capabilities and environmental variables, whereas earlier literature has theoretically outlined the possibilities of AI.

First, the current study supports hypothesis H1 by showing that AICs enhance CA in the Jordanian manufacturing sector. This finding proposes that firms can promote their marketplace by using AI resources to reduce waste, improve quality, and decrease costs. The findings of this study are in line with the extant literature (Kemp, 2024) and Krakowski et al. (2023), who found similar direct benefits for AIC in Western markets. However, our results extend this validity to the emerging market, such as Jordan, corroborating that the "AI advantage" is not limited to advanced economies (Hossain et al., 2022).

Second, our second hypothesis predicted that OA mediates the relationship between AIC and CA in the Jordanian manufacturing sector. The findings supported this hypothesis, and when OA was introduced as a mediator between AIC and CA, a positive effect was found on CA, indicating partial mediation. This indicates that while AIC directly impacts CA, a considerable portion of their value comes from enhancing firm flexibility. Our understanding is that AI serves as a "sensing tool", analyzing big data to spot market fluctuations, which then allows the firm to reallocate resources. This elucidates the "black box" phenomenon identified in prior research (Teece, 2007; Wamba, 2022); it is not the algorithm itself that generates returns, but the agility it enables. This finding is partially supported by (Wang et al., 2022; Liu et al., 2018).

Third, we suggested in H3 that ID moderates the association between AIC and CA in the manufacturing sector of Jordan. The positive moderation between AIC and CA lends credence to the notion. By demonstrating that environmental dynamism practically increases AI efficacy, this overcomes contradictions in the previous study. Our study indicates that AI's prediction accuracy becomes more valuable under these unpredictable settings, which are caused by shifting environments. AI is essentially useful in stable markets and essential for survival in dynamic ones. Our results validate the strategy described in Khan (2025) and Kumar et al. (2024).

Fourth, the current study supports hypothesis H4, as the findings underscore a robust association between the AIC and OA in the Jordanian manufacturing sector. This indicates that the more digital capabilities organizations have, the more agile they become in relation to internal processes and changes in the external environment. AI automates routine functions and provides predictive insights, freeing human capital to focus on strategic pivots. Prior studies also reported similar results, Chatterjee et al. (2021) and Wang et al. (2022), who determined digital transformation as the bedrock of contemporary agility. However, unlike Panda and Rath (2016), who focused on financial enterprises, our study confirms that this effect holds true across the industrial sector.

Finally, our results showed that OA enhances CA in the Jordanian manufacturing sector, and hypothesis H5 is confirmed. Consistent with the DC perspective, our findings support the view that the capability to identify and capture strategic opportunities is a critical factor of a CA position. In the context of the Jordanian industrial sector, this agility facilitates adaptation to regulatory changes and shifting consumer preferences more effectively than their less agile competitors do. Our results agreed with several studies in the literature (Teece, 2007; Darwish et al., 2025).

4.5.1 Research Contributions

Theoretical Contribution: This study illuminates the underlying mechanisms of digital transformation by empirically demonstrating OA as a key mediating mechanism in the relationship between AICs and CA. By situating this relationship within the RBV and DCs Perspective, the research indicates that digital resources alone do not ensure superior performance; they must be transformed into rapid operational and service-oriented responses.

Contextual Contribution: This research extends the empirical evidence of AI-enabled agility to a rapidly developing emerging-market setting. By analyzing multi-sectoral firms in Jordan, it demonstrates that the strategic value of digital informatics and dynamic service operations is not confined to advanced Western economies, thereby validating this framework for firms navigating similar economic transitions.

Managerial Contribution: The study provides highly actionable guidance by proving that AI investments yield significantly stronger returns under conditions of high ID. It demonstrates to executives that to survive turbulent market shifts, they cannot treat AI merely as an IT function; rather, they must deploy AI to prioritize real-time data processing, demand sensing, and rapid supply-chain adaptation.

5. Conclusion

The study's practical consequences provide managers in Jordan's industry sector with helpful advice.

First off, manufacturing companies may keep a CA and quickly adjust to market fluctuations by investing in strong AI skills. Second, as OA mediates the interaction between AICs and CA, managers ought to give it top priority. This will increase manufacturing companies' capacity to adapt to operational demands and market dynamics, increasing revenue and competitiveness (Sigala, 2020; Xie et al., 2022). Furthermore, OA is a key factor in success in global marketplaces, especially when technology is changing, and a company's ability to absorb new information affects how effective it is (Cho et al., 2023). A culture that welcomes change, adaptable structures, and ongoing process improvements are necessary to achieve this.

Thirdly, rather than being widely embraced, AI investments should be in line with certain strategic objectives. Fourth, in order to optimize their competitive potential, smaller businesses should adjust their strategy to fully utilize AICs by possibly bolstering their IT departments and dedicating additional resources.

Finally, our results indicate that ID positively moderates the direct relationship between AICs and CA. For firms operating under high ID, AI is not a luxury; it is a critical survival mechanism. Executives in these sectors should prioritize AI tools focused specifically on demand sensing, continuous market trend prediction, and rapid supply-chain adaptation to outmaneuver slower competitors.

Despite that, our research was comprehensive, yet it carries some limitations.

This research has a few limitations. First, it uses a cross-sectional survey to approve the proposed research model. Indeed, survey-based research has constraints, such as endogeneity problems and self-report bias. To explore the expansion of AI changes and the growth of related skills over time, we recommend that future studies use longitudinal methods.

Second, our research was limited geographically to Jordan, which helped us learn how the market is developing there. Nevertheless, our results may not apply to other countries, especially those with very advanced IT infrastructure. To clear up the effect of local cultures, economies, and laws on AI implementation, comparative studies among different countries could be performed.

Third, our research did not examine other constructs such as industry, organization size, or their knowledge in utilizing digital means. These aspects may affect how different constructs interact with each other, such as performance, AI, and agility (Chen et al., 2021; Bharadwaj et al., 2013). We recommend that future research explore how these constructs interact with our model.

Future research may look at utilizing case studies or longitudinal survey studies to assess the suggested research model. Furthermore, it may also examine the contextually energetic role of knowledge sharing in mediating or moderating the relation between AIC and CA, thereby authenticating its variability across various regions and industries.

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